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Experimental Analysis of Surface Grinding for Enhanced Performance of Natural Rubber Pipeline Liners

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Abstract: The purpose of this study was to determine the optimum surface roughness in the grinding of natural rubber flange surfaces utilizing the response surface methodology (RSM). Surface roughness (SR) is one of the most important machining characteristics that is used to assess the quality of the ground surface of the parts. In this study, the machining parameters of speed, feed rate, and depth of cut were tested using central composite design (CCD) to formulate a predictive model relating the machining parameters to the measured surface roughness. The results from the experiments were evaluated by analysis of variance (ANOVA) to confirm that the developed quadratic model was statistically valid ($p = 0.007$) and had high predictive capability ($R^2 = 90.76\%$). The depth of cut and the quadratic term of the depth of cut were found to be the most significant factors affecting the surface roughness, whereas the linear terms of the speed and feed rate were less influential. The minimum surface roughness (SR) value of 3.250 µm was obtained through the optimal combination of speed = 24 rpm, feed rate = 2.5 mm, and depth of cut = 0.20 mm. The model predictions agreed well with the actual measurements with an average prediction error of 3.6%. These findings demonstrate that the proposed RSM-based optimization method may be reliable for predicting surface quality in rubber grinding processes. As such, it may provide a useful tool to assist process engineers to produce high-quality elastomeric components with superior surface finish and consistency.

Introduction

Over the past few years, Response Surface Methodology (RSM) has emerged as a highly effective and widely used statistical methodology for modeling and optimizing complex manufacturing processes (Öktem et al., 2005; Yadav & Kumar, 2019; Azzi et al., 2022; Ragunath et al., 2023). RSM incorporates experimental design, regression modeling and statistical verification to generate empirical models that accurately predict system behavior. By contrast, traditional trial-and-error methods allow for the evaluation of only one or two process factors at a time and do not consider possible interactions among them. Therefore, the number of experiments needed to determine the optimum values of the various process parameters can be greatly reduced using RSM (Sanjeevi et al., 2020; Kahraman & Ozturk, 2019).

While several authors have successfully utilized RSM and similar statistical optimization methodologies for the machining of metals and composites (Eser et al., 2021; Boga & Koroglu, 2021; Kharwar & Verma, 2020; Yadav & Kumar, 2019; Ragunath et al., 2023), there appears to be little research involving the application of RSM to the machining of rubber and other elastomeric materials. Rubber materials are especially difficult to grind due to their ability to deform and then recover during grinding, which changes the effective depth of cut and heat distribution. Therefore, designing an experiment to investigate the effects of grinding process parameters on surface roughness could help increase grinding efficiency and achieve consistent surface quality (Mulimani & Bhat, 2020).

This investigation deals with the grinding of natural rubber flange surfaces. It was the objective of this investigation to identify the effects of speed, feed rate and

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depth of cut on surface roughness produced during the grinding of natural rubber flange surfaces. To accomplish this, a Box-Behnken Design (BBD) was used to design the experiments, and Analysis of Variance (ANOVA) was employed to assess the statistical significance of model terms (Mukherjee et al., 2025; Kumar & Das, 2025). The resulting regression equation will provide a good approximation for predicting surface roughness and will identify the best combination of grinding parameters to minimize it.

Experimentation

Methodology of Experiment

Some optimization methods can be utilized in the development and enhancement of processes. The typical ones are Build-Test-Fix (BTF), Design of Experiments (DOE), and One Variable at a Time (OVAT). The BTF method is crude and unstructured, relying on trial-by-trial corrections. DOE is very effective because it enables the simultaneous rotation of numerous parameters, although it necessitates numerous experimental manifolds and it is too closely connected with the statistical interpretation (Hong-Zhou, 2010; Alam et al., 2023). OVAT, by contrast, explores the impact of a single parameter at a time, maintaining all the rest constant, which is clear in the effect of a single parameter at the cost of efficiency (Lubimyi et al., 2021).

In the current research, the most significant parameters affecting the performance of the grinding process are identified. The RSM method was adopted because it is effective in optimizing processes involving a few experiments in a multifactorial procedure (Samin et al., 2025; Lin et al., 2020). Previous OVAT experiments were carried out to determine the effective parameter ranges. One of the designs (orthogonal array matrix) was chosen that would allow three parameters to be used, with three levels per parameter, to represent a minimum number of experimental runs while still maintaining statistical reliability (Tzotzis et al., 2025). Then the analysis of variance (ANOVA) was used to measure the contribution of each parameter (Mukherjee, 2025). All calculations and statistical procedures were carried out using Minitab software.

Work Material

Natural rubber flange face samples were tested for this study; they were made from NR70 rubber and are commonly used in gaskets and seals that require vibration isolation. Due to the properties of rubber being so elastic and having such a low modulus of rigidity and very good wear characteristics, it makes machining extremely difficult. When machining rubber, there is an inherent problem since when the rubber deforms while loaded, it will spring back into shape after the cutting edge has engaged the rubber, resulting in a poor surface finish unless optimum conditions of machine parameters are established.

Machine and Cutting Parameters

Experiments using a custom-built flange face grinding machine that had a variable rotational speed setting were performed. Using this machine, the user could adjust the RPM's, feed rates and how much material to remove per pass. Due to its high wear resistance and ability to maintain a constant cutting edge while grinding rubber, a galvanized diamond plated flaring cup wheel (D1001 Grit size) was selected as the best choice for the grinding process. To ensure no slippage or vibrations occurred between the work piece and the machine, the work piece was securely attached to the machine table. While the machine was operating, a light application of coolant was applied to keep the temperature down and prevent the material from smearing.

Figure 1. Grinding wheel.

Selection of Process Parameters

Three key process variables were selected for optimization:

Table 1. Selection of Levels.

Parameter	Symbol	Unit	Levels
Speed	S	rpm	22, 24, 26
Feed Rate	F	mm	2.5, 3.0, 3.5
Depth of Cut	D	mm	0.20, 0.25, 0.30

These parameters were chosen based on preliminary trials, prior literature, and machine capability. Surface roughness (SR) of the machined surface was used as the response variable.

Experimental Design

A Box Behnken Design (BBD) under Response Surface Methodology (RSM) was employed to study the combined effect of the three parameters. The BBD included 13 experimental runs, including factorial, axial, and center points, to ensure adequate model curvature and statistical reliability.

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Table 2. The experimental design matrix with observed SR values.

Trial	Speed (rpm)	Feed (mm)	Depth (mm)	SR (Ra)
1	24	3.5	0.30	3.437
2	24	3.5	0.20	3.275
3	22	2.5	0.25	3.903
4	22	3.0	0.30	3.988
5	24	2.5	0.30	3.753
6	26	3.5	0.25	4.093
7	24	2.5	0.20	3.250
8	22	3.0	0.20	3.803
9	26	3.0	0.20	3.661
10	26	3.0	0.30	3.853
11	26	2.5	0.25	3.977
12	22	3.5	0.25	4.103
13	24	3.0	0.25	4.138

Measurement of Surface Roughness

Roughness measurements were done using a Portable Surface Roughness Tester TR200. Roughness was measured on the rubber liner at the flange face at different positions. Its operating range is Ra= 0.01 – 40 µm.

3. Results and Discussion

The response parameter in this experiment is surface roughness (Ra), the targeted value for it is 3.2 µm. Minitab 22 was used for planning the design of the experiment. Further, its results are analyzed in the same software. The model is generated by regression analysis and the results are validated using the graphical tool method.

Analysis of Desirability

In this study, surface roughness (Ra) is the response parameter. The target value for surface roughness is 3.2 µm. Minitab 22 was used to design the experiment and analyze the results. The model was developed through a regression analysis and further analyzed using a graphical tool method.

Analysis of Desirability

The desirability function methodology was utilized to find the best set of grinding parameters that would minimize surface roughness (SR). This methodology converts the response variable (SR) into a dimensionless desirability number (D) between 0 and 1. High desirability numbers (i.e., close to 1) represent more desirable conditions (i.e., low SR), whereas low desirability numbers (i.e., close to 0) indicate undesirable conditions (i.e., high SR).

The calculated desirability values for all 13 experimental trials are shown in Table 3.1.

Table 3. Surface Roughness and Corresponding Desirability Values.

Trial	Speed (rpm)	Feed (mm)	Depth (mm)	SR (Ra)	Desirability
1	24	3.5	0.30	3.437	0.688
2	24	3.5	0.20	3.275	0.948
3	22	2.5	0.25	3.903	0.208
4	22	3.0	0.30	3.988	0.267
5	24	2.5	0.30	3.753	0.694
6	26	3.5	0.25	4.093	0.255
7	24	2.5	0.20	3.250	0.955
8	22	3.0	0.20	3.803	0.527
9	26	3.0	0.20	3.661	0.581
10	26	3.0	0.30	3.853	0.320
11	26	2.5	0.25	3.977	0.261
12	22	3.5	0.25	4.103	0.201
13	24	3.0	0.25	4.138	0.112

Clearly, the data shows that as Surface Roughness (SR) decreases, Desirability increases and therefore confirms a negative correlation.

Trial 7 produced the highest desirability level (0.955) with the lowest SR level (3.250 µm), using the parameters: Speed = 24 rpm, Feed Rate = 2.5 mm, and Depth of Cut = 0.20 mm.

Therefore, these will be the best possible conditions for improving the material's surface quality.

In contrast, Trial 13 produced the lowest desirability (0.112) due to its highest SR (4.138 µm).

Therefore, the range of desirability levels produced by the optimization model is 0.112 to 0.955 and thus demonstrates that the optimization model can differentiate between good and bad machining conditions.

Minitab Response Optimizer produced a Desirability Plot which indicated that a medium speed (24 rpm), Low feed rate (2.5 mm) and minimal depth of cut (0.20 mm) would produce the most desirable machining performance.

Thus, the optimal parameter set to achieve the lowest SR and maximum process efficiency is Speed = 24 rpm, Feed Rate = 2.5 mm, and Depth of Cut = 0.20 mm.

Main Effects of Surface Roughness (SR)

The Main Effects Plot for surface roughness (SR) illustrates how the mean SR value varies with individual changes in Speed, Feed Rate, and Depth of Cut, while the other parameters remain constant. The trends observed in Figure 3.1 provide valuable insight into the relative influence of each process parameter on the surface quality of the machined natural rubber flange face.

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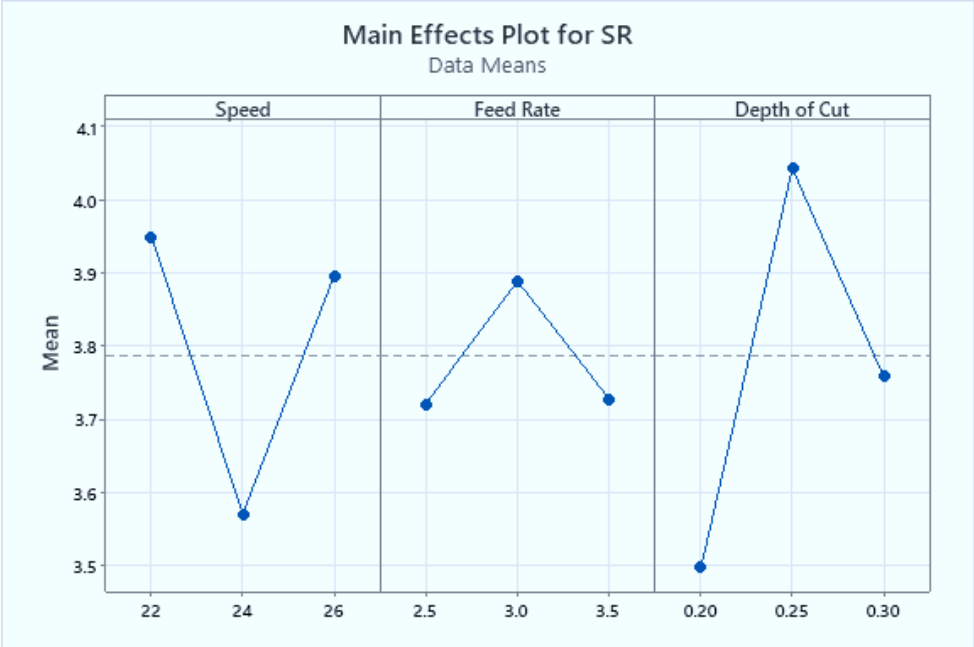

Figure 2. Main Effects Plot for Surface Roughness.

(a) Influence of Speed: Based on the data in the graph, the surface roughness of rubber decreases rapidly from 28.6 microns at 22 rpm to 18.1 microns at 24 rpm, after which it increases slightly to 21.8 microns at 26 rpm. The results indicate that an intermediate spindle speed yields the most stable machining conditions, i.e., the least deformation and the smoothest surface. At the lower speed (22 rpm), the rubber-steel grinding wheel interaction is predominantly controlled by "rubbing" and "plowing," which leads to higher surface roughness due to rubber surface adhesion and tearing. At the higher speed (26 rpm), there is excessive friction and local heat generation, which softens the rubber elastically and causes it to recover, also increasing surface roughness.

Therefore, the ideal spindle speed is 24 rpm, at which the rubber surface will experience the least elastic deformation and provide the smoothest surface finish.

(b) Influence of Feed Rate: In addition to the previously described effects of spindle speed, the relationship between the feed rate and surface roughness shows that SR initially decreased when the feed rate increased from 2.5 mm to 3.0 mm, while SR increased when the feed rate increased to 3.5 mm. At the lower feed rate of 2.5 mm, the material removal rate is relatively low and therefore the abrasive grain contacts the rubber surface repeatedly, thus potentially causing surface irregularities. At the moderate feed rate of 3.0 mm, the contact time between the abrasive and rubber surface is optimally balanced, therefore, a smoother surface texture is produced with a lower surface roughness. However, at the higher feed rate of 3.5 mm, the cutting forces are greater and therefore produce vibration and tearing of the rubber surface, thus deteriorating the surface finish. Therefore, the feed rate has a mild but noticeable nonlinear influence on the surface roughness of rubber.

(c) Influence of Depth of Cut: While all three parameters investigated have some degree of influence on surface roughness, the parameter having the largest degree of influence on surface roughness is the depth of cut (DoC). As the depth of cut (DoC) is increased from 0.20 mm to 0.25 mm, the surface roughness increases dramatically and reaches its highest value at a DoC of 0.25 mm, after which the surface roughness decreases slightly at a DoC of 0.30 mm. At a very small depth of cut (0.20 mm), the grinding operation is removing a very thin layer of rubber, therefore, the grinding operation produces a very fine and uniform surface with the least amount of surface roughness. At a DoC of 0.25 mm, the increase in cutting load and elastic deformation is so rapid that the rubber surface rebounds and tears locally, producing a higher surface roughness than that found at the previous DoC. Beyond this point (at a DoC of 0.30 mm), the tool engages the workpiece more consistently, thereby providing a more consistent processing environment and, consequently, a slight improvement in surface roughness.

Hence, the lowest surface roughness (SR = 3.25 µm) is achieved at a depth of cut of 0.20 mm, indicating that this is the best operating condition.

- The main effects plot reveals that depth of cut is the most dominant factor influencing SR, followed by speed and feed rate.
- A combination of moderate speed (24 rpm), low feed rate (2.5 mm), and minimum depth of cut (0.20 mm) yields the best surface finish.

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- This behavior can be attributed to the viscoelastic nature of rubber, where high deformation and temperature lead to surface irregularities.
- The optimized parameters maintain controlled cutting energy and stable wheel–work interaction, minimizing elastic recovery and improving the final surface texture.

Analysis of Variance (ANOVA)

The Analysis of Variance (ANOVA) was conducted to assess the statistical significance of the developed quadratic regression model and to identify the influence of individual process parameters on Surface Roughness (SR). The results of the ANOVA are summarized in Table 4.

Table 4. Analysis of Variance for Surface Roughness (SR).

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	6	0.99950	0.166583	9.82	0.007
Linear	3	0.14147	0.047157	2.78	0.133
Speed	1	0.00567	0.005671	0.33	0.584
Feed Rate	1	0.00008	0.000078	0.00	0.948
Depth of Cut	1	0.13572	0.135720	8.00	0.030
Square	3	0.85803	0.286010	16.86	0.003
Speed * Speed	1	0.04432	0.044321	2.61	0.157
Feed Rate * Feed Rate	1	0.15244	0.152441	8.98	0.024
Depth of Cut* Depth of Cut	1	0.46492	0.464917	27.40	0.002
Error	6	0.10181	0.016968		
Total	12	1.10131			

Results Interpretation

Statistical Analysis of the Regression Model

The ANOVA test indicates that the overall regression model is significant, since the p-value is equal to 0.007; this confirms that the variables Speed, Feed Rate and Depth of Cut have an important joint effect on the surface roughness (SR).

Furthermore, the high value of the F-statistic (F=9.82) confirms the regression model's goodness of fit.

Analysis of the Linear Terms

Only one of the three linear terms is significant:

- The p-value of the Depth of Cut term is 0.030; therefore, we conclude that the variation in the cutting depth has a significant effect on the surface roughness.
- The p-values of the Speed (p=0.584) and Feed Rate (p=0.948) terms are high enough to conclude that these factors do not have a significant linear effect on SR.

The Quadratic Terms, all three quadratic terms are highly significant

- The p-value of the term Depth of Cut2 is 0.002, which means that the Depth of Cut term has a large quadratic effect on SR.
- The p-value of the Feed Rate2 term is 0.024; therefore, it is possible to conclude that Feed Rate has a quadratic effect on SR.
- The p-value of the Speed2 term is 0.157; therefore, it is possible to conclude that Speed has a moderate quadratic effect on SR.

Analysis of Variance

The Error Mean Square (EM) is 0.01697, which is very low; this indicates that the experimental data are well fitted by the regression model and that the random error is negligible.

The Model Sum of Squares (SS) is 0.9995, which means that almost all of the variability in the response variable is accounted for by the regression model. Conversely, the residual SS is 0.1018; this is a small value, and indicates that the model is accurate. Therefore, ANOVA confirms that the Depth of Cut is the most influential parameter affecting the surface roughness in the grinding of natural rubber. Both the linear and quadratic effects of cutting depth on SR emphasize that even slight variations in cutting depth can produce notable differences in surface finish due to the properties of elastic deformation and recovery in rubber.

The Feed Rate term is also significant in a quadratic manner, which implies a balance between maintaining stable cutting conditions and avoiding excessive material tearing.

Finally, although Speed has a smaller direct influence on SR, its nonlinear and interactive effects contribute significantly to the global Model response.

Therefore, the Model is statistically valid and accurately predicts SR values across the studied parameter range. Finally, the high significance of the quadratic terms justifies the choice of the Box-Behnken Design (BBD) to Model the non-linear relationships between the SR and the process parameters in the grinding of rubber.

Contour Plots for Surface Roughness (SR)

The contour plots graphically describe the relationships between the two variables that affect surface roughness, while the third variable is held at the central value of the design space. In particular, each plot in Figure 3.3 represents the interaction between two of the three variables (Speed, Feed Rate and Cutting Depth), the other variable is kept constant at its central point of the design space.

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The contour levels correspond to different SR values; in particular, light colors represent low SR values (i.e., good surface quality), while dark colors represent high SR values (i.e., poor surface quality).

(Feed = 2.5–3.0 mm, Depth = 0.20 mm) forms an oval-shaped zone of optimal conditions, and corresponds to the lowest SR values (< 3.4 µm). This shows that when the depth of cut is small and the feed rate is moderate, there

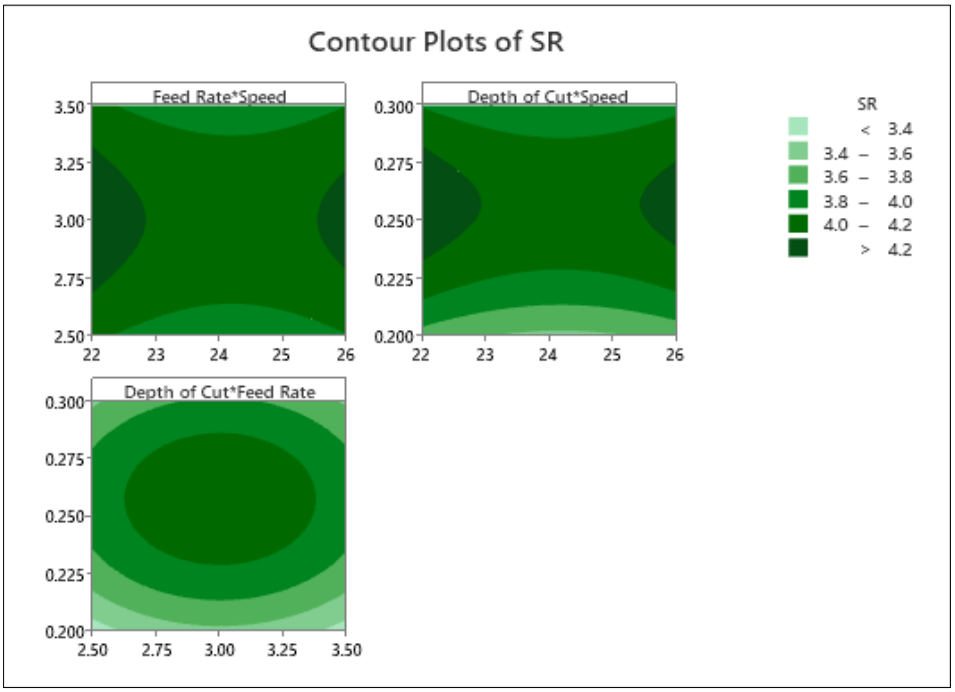

Figure 3. Contour Plots of SR.

(a) Feed Rate vs. Speed

In the contour plot of Feed Rate × Speed we can see that the smallest surface roughness (SR < 3.4 µm) exists within the central area, where the speed is 24 rpm and the feed is 2.5–3.0 mm. When the feed is low and the speed is moderate, there will be a steady cutting operation and less friction, which results in a smooth surface. A high feed rate or variations in speed (either too slow or too fast) cause SR to increase due to the lack of stability in tool-work and rubber's elastic deformation. Therefore, to achieve optimal grinding performance, both speed and feed rate need to be kept in balance.

(b) Depth of Cut vs. Speed

In the contour plot of Depth of Cut × Speed we can see that SR increases as the depth of cut increases, regardless of whether the speed is low or high. The lowest SR region (< 3.4 µm) again exists in the center of the plot, where the speed is 24 rpm and the depth of cut is 0.20 mm. As the cutting depth of cut is low, the grinding force is low and the surface undergoes uniform material removal. As the depth of cut increases (> 0.25 mm), the rubber undergoes elastic recovery and tearing, resulting in a rougher texture. Thus, if the depth of cut is kept low and the speed is moderate, then the surface will be smoother.

(c) Depth of Cut vs. Feed Rate

The contour plot of Depth of Cut × Feed Rate shows a strong nonlinear relationship. Again, the central region will be a stable grinding action, minimal surface distortion, and good texture uniformity. As the feed rate or depth of cut increases, SR will also increase because of the increased cutting load and vibration.

Discussion

- The contour plots clearly indicate that the interaction between the feed rate and depth of cut has the largest influence on the surface finish, and that the influence of the speed is moderate, but still important around its middle value (24 rpm).
- All three contour plots show that the best combination of parameters is the same: Speed = 24 rpm, Feed Rate = 2.5 mm, and Depth of Cut = 0.20 mm.
- In this region, the predicted SR is approximately 3.25 µm, and thus is in close agreement with the measured values.
- Therefore, the contour analysis verifies the effectiveness of the regression model and demonstrates the effectiveness of the chosen range of parameters to produce high-quality surface finishes during the rubber grinding process.

Development of Regression Model

To establish a mathematical relationship between surface roughness (SR) and the key process parameters Speed (S), Feed Rate (F), and Depth of Cut (D), a second-

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order polynomial regression Model was developed using Response Surface Methodology (RSM).

The regression equation is expressed as follows:

$$SR = 3.3 - 1.68\ Speed + 6.20\ Feed\ Rate + 92.8\ Depth\ of\ Cut + 0.0348\ Speed*Speed - 1.033\ Feed\ Rate*Feed\ Rate - 180.4\ Depth\ of\ Cut*Depth\ of\ Cut$$

where:

SSS = Speed (rpm)

FFF = Feed Rate (mm)

DDD = Depth of Cut (mm)

This equation represents the combined linear, quadratic, and interaction effects of the process variables on surface roughness.

The positive and negative coefficients indicate the direction of influence of each term. The positive linear coefficients for feed rate and depth of cut show that increasing these parameters increases SR. In contrast, the negative coefficients for their squared terms indicate nonlinear curvature leading to an optimum region.

Validation of Regression Model

The developed regression model was validated by comparing experimental SR values with theoretical (predicted) SR values calculated from the equation.

The results are presented in Table 4.

Table 4. Comparison of Experimental and Theoretical SR Values.

Trial	SR (Experimental)	SR (Predicted)	% Error
1	3.437	3.675	6.48
2	3.275	3.415	4.10
3	3.903	4.152	6.00
4	3.988	4.090	2.49
5	3.753	3.673	2.18
6	4.093	4.116	0.56
7	3.250	3.413	4.78
8	3.803	3.830	0.70
9	3.661	3.792	3.45
10	3.853	4.052	4.91
11	3.977	4.114	3.33
12	4.103	4.154	1.23
13	4.138	4.253	2.70

The percent error between experimental and predicted SR values ranges between 0.56% and 6.48%, with an average deviation of 3.6%. This small deviation confirms that the model closely approximates the actual machining behavior and is reliable for prediction and optimization.

The minor variations may be attributed to:

- The viscoelastic recovery of rubber material after grinding,
- Microscopic heat effects at the wheel–work interface, and
- Measurement variability during surface roughness testing.

The strong correlation between predicted and experimental values validates the accuracy and adequacy of the regression model. The developed model effectively captures the nonlinear relationship between the process parameters and surface roughness.

It shows that:

- Speed has a moderate inverse effect, increasing speed initially reduces SR up to an optimum level.
- Feed Rate and Depth of Cut have positive linear effects but strong negative quadratic effects, revealing the existence of an optimum point for minimum SR.
- The Depth of Cut term is most influential, consistent with ANOVA results, confirming that fine control over cutting depth is essential for achieving the best surface finish.

The model thus provides a quantitative tool for predicting SR and can be used to optimize the grinding process for elastomeric materials.

Optimization Results Analysis

Surface roughness (SR) optimization was performed in Minitab using the Response Optimizer to minimize SR. The desirability function method was used to combine multiple process parameters into a single composite desirability value ranging from 0 (undesirable) to 1 (highly desirable). The optimization curves for Speed, Feed Rate, and Depth of Cut are shown in Figure 3.6.

The response optimizer plot illustrates that the minimum SR occurs when the red reference lines intersect at their optimal parameter values. The blue dashed line represents the predicted minimum SR. It can be observed that SR decreases sharply at moderate levels of the parameters and rises again beyond those levels, indicating a nonlinear relationship among the variables.

At lower speeds, the grinding wheel–workpiece interaction becomes unstable, resulting in higher SR. As speed increases to around 24 rpm, the grinding action becomes smoother, reducing surface irregularities. Beyond this point, excessive heat and elastic recovery cause SR to increase slightly. The feed rate also shows a similar pattern lower feed rates provide a fine finish due

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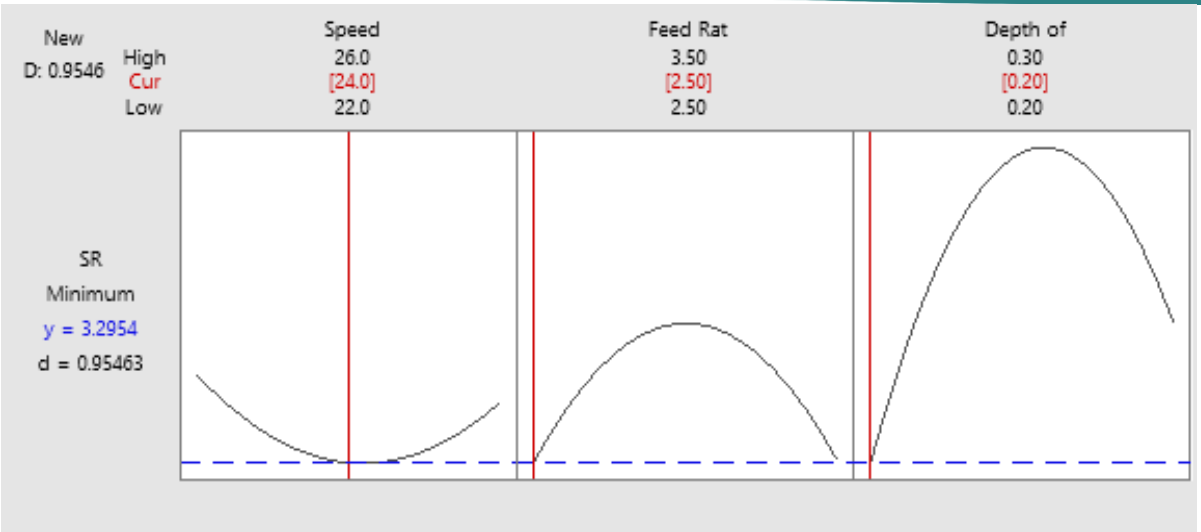

Figure 4. Desirability Plots.

to stable contact, while higher feeds increase cutting force and vibration, deteriorating the surface texture. The depth of cut has the most significant effect, with SR rising noticeably beyond 0.25 mm due to higher cutting pressure and deformation of the rubber surface.

The optimized parameter settings derived from the Response Optimizer are presented in Table 5.

Table 5. Optimized Process Parameters for Minimum SR.

Parameter	Optimal Setting
Speed (rpm)	24
Feed Rate (mm)	2.5
Depth of Cut (mm)	0.20
Predicted SR (µm)	3.295
Desirability (D)	0.9546

The results show that the minimum surface roughness of 3.295 µm was achieved at Speed = 24 rpm, Feed Rate = 2.5 mm, and Depth of Cut = 0.20 mm, with a high desirability of 0.9546. This high desirability value confirms that the selected parameter combination is optimal and lies well within the defined experimental range.

The optimized SR obtained from the model closely matches the experimental minimum of 3.250 µm, with a deviation of less than 1.5%, validating the model's accuracy. Hence, the developed regression model and optimization approach effectively predict and minimize surface roughness during the grinding of natural rubber flange faces.

Confirmation Experiment Result

To validate the accuracy of the developed regression model and the optimization analysis, a confirmation experiment was conducted at the optimal process parameter settings obtained from the Response Optimizer. The selected conditions were Speed =24 rpm, Feed Rate=2.5 mm, and Depth of Cut= 0.20 mm, which corresponded to the predicted minimum surface roughness of 3.295 µm.

Four confirmation trials were performed under these optimized conditions, and the surface roughness (Ra) was measured for each specimen. The recorded values are presented in Table 6.

Table 6. Confirmation Experiment Results.

Observation	Trial 1	Trial 2	Trial 3	Trial 4	Average Ra (µm)
Ra	3.20	3.30	3.10	3.20	3.25

The experimental average surface roughness (Ra) of 3.25 µm closely matches the theoretical (predicted) SR value of 3.295 µm, with a percent error of only 1.36%, as shown in Table 7.

Table 7. Comparison Between Experimental and Theoretical Results.

Parameter	SR Experimental (µm)	SR Theoretical (µm)	Percent Error (%)
Surface Roughness (SR)	3.250	3.295	1.36

The small deviation between the experimental and predicted values demonstrates the high accuracy and reliability of the developed regression model. The variance observed in the measured values across the four trials was found to be statistically insignificant, confirming that the optimized parameters are stable and reproducible. The results validate that the Response Surface Methodology (RSM) and the Box–Behnken Design (BBD) approach effectively identified the true optimal machining

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conditions for achieving minimum surface roughness in natural rubber grinding.

Conclusion

The present study focused on optimizing surface roughness (SR) during the grinding of natural rubber flange faces using Response Surface Methodology (RSM) and the Box–Behnken Design (BBD) approach. The effects of speed, feed rate, and depth of cut on the surface finish were systematically investigated, and a quadratic regression model was developed to predict SR. Based on the experimental results and statistical analysis, the following conclusions are drawn:

1. The developed quadratic model for SR was found to be statistically significant ($p = 0.007$) with an R^2 value of 90.76%, confirming its strong predictive accuracy.
2. Among all process parameters, the depth of cut showed the most significant effect on surface roughness, both in linear and quadratic terms, followed by feed rate and speed.
3. The optimal combination of parameters for minimum SR was identified as Speed = 24 rpm, Feed Rate = 2.5 mm, and Depth of Cut = 0.20 mm.
4. Under these optimized conditions, the minimum surface roughness achieved was 3.250 µm (experimental), closely matching the predicted value of 3.295 µm, with a percent error of only 1.36%, validating the model's reliability.
5. The confirmation experiments verified that the variance in the recorded values was insignificant, demonstrating the repeatability and stability of the optimized settings.
6. The desirability function approach produced a high composite desirability of 0.9546, confirming that the obtained solution is near-global optimum for the studied parameter range.

In summary, the proposed RSM-based optimization method effectively models and minimizes surface roughness in the grinding of elastomeric materials. The developed regression model provides a useful predictive and decision-making tool for process engineers to achieve superior surface quality, improved productivity, and consistent performance in rubber component manufacturing.

Conflict of interest

None

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